Intelligent Tool Condition Monitoring in milling operation

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Abstract: One of the most important features of the modern machining system in an "unmanned" factory is to change tools that have been subjected to wear and damage. An integrated system composed of multi-sensors, signal processing device and intelligent decision making plans is a necessary requirement for automatic manufacturing process. An intelligent tool wear monitoring system for milling operation will be introduced in this report. The system is equipped with four kinds of sensors, signal transforming and collecting apparatus and microcomputer. A unique ANN (artificial neural network) driven fuzzy pattern recognition algorithm has been developed from this research. It can fuse the information from multiple sensors and has strong learning and noise suppression ability. This lead to successful tool wear classification under a range of machining conditions.

Key Words: Condition monitoring; feature extraction; fuzzy pattern recognition; neural network; sensor fusion; tool wear classification.

1. Introduction: Metal cutting operation compounds a large percentage of the manufacturing activity. One of the most important objective of metal cutting research is to develop techniques that enable optimal utilization of machine tools, improved production efficiency, high machining accuracy and reduced machine downtime and tooling cost be possible. Tool condition monitoring is certainly the important monitoring requirement of unintended machining operations. It has been estimated that the development of methods to reliably detect the end of tool life could result in an increase of cutting speed from 10% to 50%, a decrease in cutting time, savings in tool changing time, and overall savings of 10 to 40% [1].

Many kind of sensing techniques have been used to monitor tool condition. An approach was developed for in-process monitoring tool wear in milling using frequency signatures of the cutting force [2]. The approach was based on the variations of the magnitude of cutting force harmonics along with flank wear. Some special parameters were used for detecting tool wear [3]. By processing the force signals, three characteristic parameters, the derivative of force wave form, power and coefficient of auto-correlation had been found to be relevant to tool wear. A relationship between the spindle motor current and the tool flank wear in turning operation was developed by Y. S. Liao [4]. It was found that the motor current increased nearly linearly from the beginning to the end of the tool's useful life if only one material was machined. Acoustic emission (AE) has been

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recognized as a promising means for on-line tool condition monitoring. The skew and kurtosis of the AE-RMS were related with the increase of the tool flank wear [5,6]. The dominant frequency components of AE signal are generally below 500 kHz. In this range the spectra amplitudes were found to increase with the accumulation of tool wear [7]. A scheme known as time domain averaging (TDA) was applied to process AE signal for on-line sensing of tool wear in face milling [8]. Experiment results showed that the mean AE-RMS energy had an increasing trend with the growth for natural insert wear. Statistical techniques were used to combine power spectrum estimates with higher-order spectrum (HOS) estimates to extract features [9]. Those features were applied to discriminate and classify vibration signals from new and slightly used drill bits in a drill wear study. The amount of tool wear in face milling was related to the change of the envelope (signal boundary) of the vibration signal [10]. Grieshaber et al [11] used spectral density and spectral area of vibration signal to identify tool wear in face milling.

It has been widely accepted now that under varying machining conditions, the information required to make reliable decisions on the tool wear state can hardly be available by using single sensor information. Sensor fusion is attractive since loss of sensitivity of one of the sensors can be compensated by other sensors. A discriminate function technique was used to combine force signal with acoustic emission information to monitor cutting tool condition [12]. Neural networks was proved to be suitable for integrating information from acoustic emission and cutting force sensors to predict tool wear in turning operation [13]. The sensor signal patterns and the tool wear states were successfully associated. Choi et al [14] developed a neural network-based real-time tool wear monitoring system. P.G.Li et al. [15] used fuzzy pattern recognition algorithm to monitor drilling tool wear. The thrust and torque are selected as the features relevant to drill wear and the relationship between these features and drill wear was found from fuzzy manipulation.

In this study, an ANN driven fuzzy pattern recognition algorithm was developed to accomplish multi-sensor information integration and tool wear states classification. By imitating the thinking and judging modes of human being, the technique shows some remarkable characteristics. Definite mathematical relations between tool wear states and sensor information are not necessarily needed. The effects caused by experimental noise can also be decreased greatly. The established monitoring system provided accurate and reliable tool wear classification results over a range of cutting conditions.

2. Tool condition monitoring system: The experiments were carried out on a Cincinnati Milacron Sabre 500 machining center. Like many other modern machine tools, it delivers a signal that is proportional to the power consumption rating of the spindle motor (up to 6.1 volts corresponding to 100% of the full power of the motor). A KISTLER 9257B force dynamometer was used to measure cutting forces, F_x, F_y, F_z, in three mutually perpendicular directions. The dynamometer has a measuring range of 5000 N in each direction, linearity of 1%, stiffness of 350 N/μm in the Z direction and 1000 N/μm in the X and Y directions and a resonant frequency of 4kHz. The acoustic emission (AE)

measuring apparatus includes an AE sensor and a signal processing device. The AE sensor has a measuring frequency range of 100kHz - 2MHz. An analogue module receives the input from the pre-amplifier and provides outputs of both amplified AE analogue signals and AE-RMS signals.

The power consumption signal

The cutting force signal

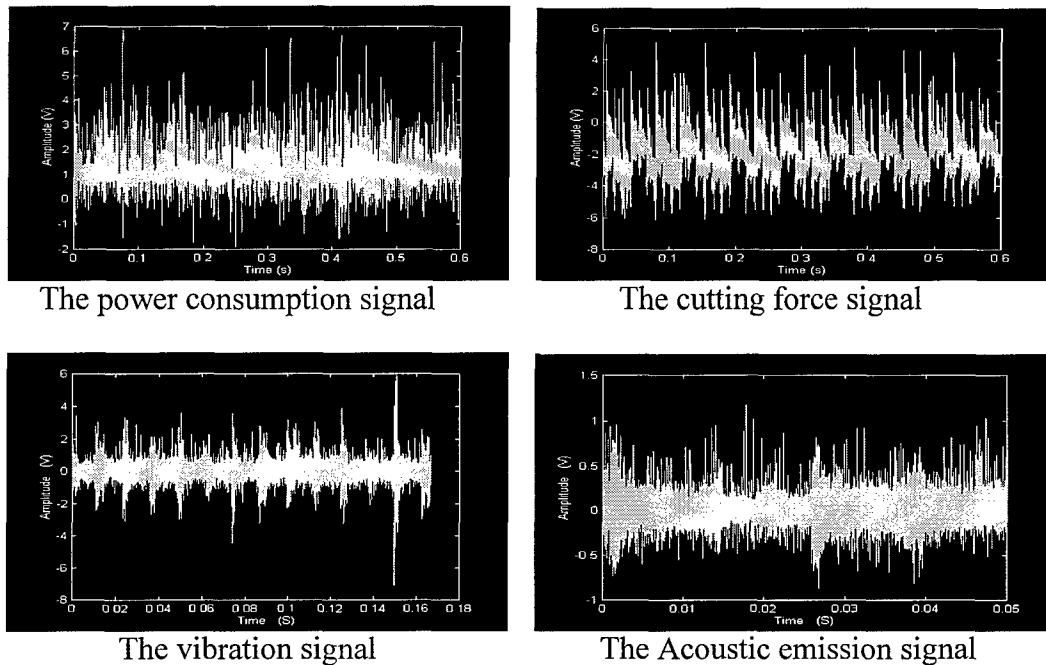The vibration signal

The Acoustic emission signal

Fig.1 Tool condition monitoring sensor signals

An accelerometer was mounted in the feed direction. The sensor has a frequency response of 5 - 33 kHz, mounted resonant frequency 50 kHz. Fig.1 shows the power consumption, cutting force F_x (in the cutting direction), vibration and acoustic emission signals respectively. The tool wear monitoring system is composed of four types of sensors, signal amplifying and collecting devices and the main computer, as shown in Fig.2.
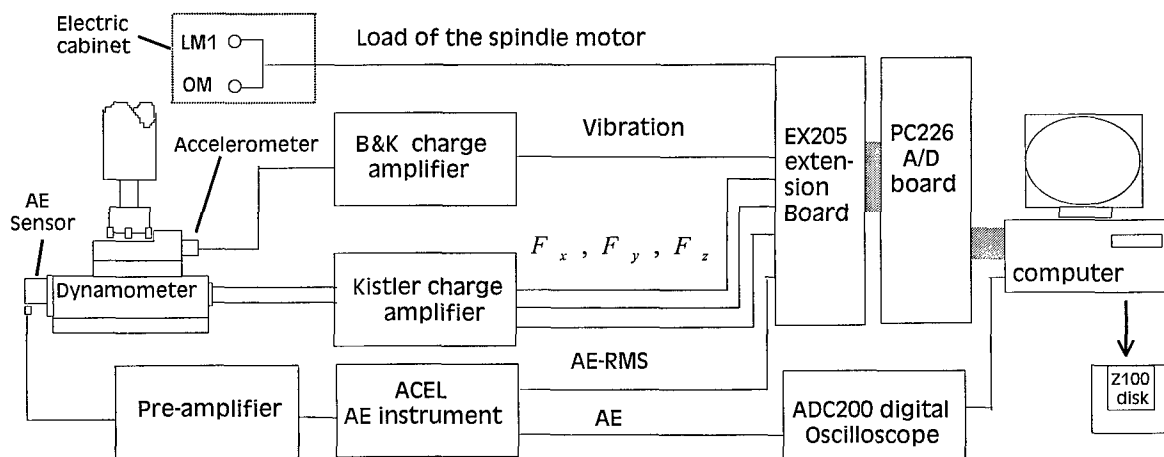

Fig.2 The tool condition monitoring system for milling operation

The dynamometer was fixed on the table of the machine with the workpiece mounted on the top of it. The accelerometer and the AE sensor were mounted on the side of the workpiece and the dynamometer respectively. The power consumption, vibration and cutting force signals were collected by the computer through an A/D board at 5 kHz, 300 kHz and 30 kHz respectively. The AE signal sampling was accomplished by using the digital oscilloscope at a frequency of 12 MHz.

3. ANN driven fuzzy pattern recognition: Tool condition monitoring is a pattern recognition process in which the characteristics of the tool to be monitored are compared with those of the standard models. The process is composed of the following parts: feature extraction, determination of the membership functions, calculation of the fuzzy distance, learning and tool wear classification.
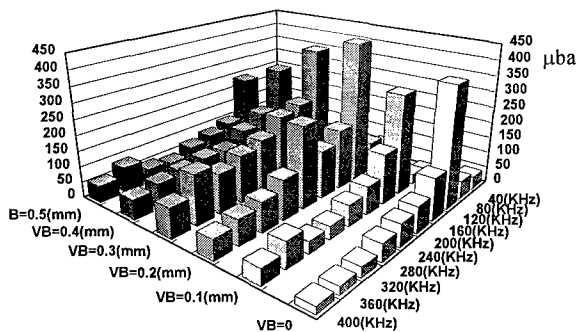
3.1 Feature extraction: Features extracted from the time domain and frequency domain for pattern recognition are as follows. Power consumption signal: mean value; AE-RMS signal: mean value, skew and kutorsis; Cutting force, AE and vibration: mean value, standard deviation and mean power in 10 frequency ranges within the working frequencies. As an example, Fig.3 shows several features (under cutting condition1*) in time and frequency domain. It can be seen that both the amplitude and the distribution pattern can represent the development of tool wear.
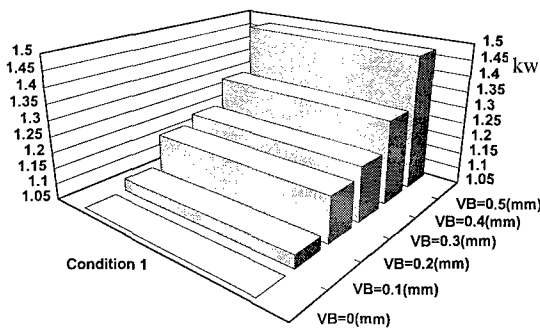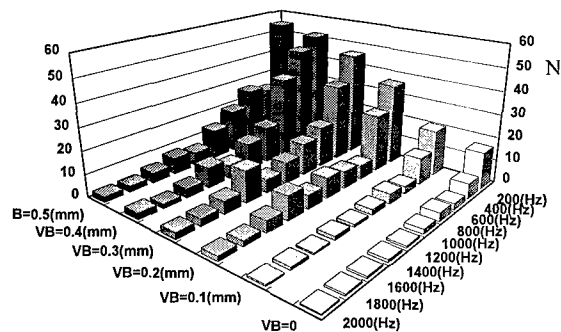

Mean value of the power
consumption signal
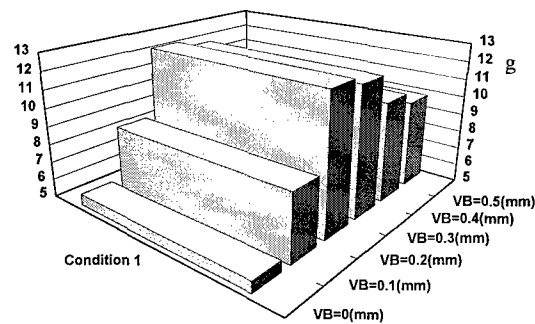
Standard deviation of the
vibration signal

Spectra of the AE signal   Spectra of cutting force (F_x) signal
Fig.3 Features extracted from different sensor signals

3.2 Determination of the membership functions of the features:

The features of signals can reflect the tool wear states. For the standard model (groups of inserts with standard flank wear values), the j-th feature of the i-th model is a fuzzy set A_{ij}. Theoretical analysis and experimental results show that these features can be regarded as normal distribution fuzzy sets. The membership function of the fuzzy set A_{ij} can be represented as:

$$
A_{ij}(x) = e^{-\frac{(x - a_{ij})^2}{2\sigma_{ij}^2}} \qquad a_{ij} - \sqrt{2}\sigma_{ij} < x < a_{ij}
$$
$$
= 1 \qquad a_{ij} \le x \le b_{ij} \qquad\qquad \text{.....................(1)}
$$
$$
= e^{-\frac{(x - b_{ij})^2}{2\sigma_{ij}^2}} \qquad b_{ij} < x < b_{ij} + \sqrt{2}\sigma_{ij}
$$
$$
= 0 \qquad \text{for other values of X}
$$

where a is the mean value and σ is the standard deviation. In order to determine the values of the coefficients in the formula, several groups of inserts possessing standard wear values were used in milling operations. K groups of specimens were drawn for the j-th feature, then for each group the mean value $\overline{x}_{ijt}$ and the standard deviation σ_{ijt} can be calculated (t=1,2,...,k). So a_{ij} and b_{ij} can be set as the maximum and minimum values of $\overline{x}_{ijt}$ and σ_{ij}^2 can take the mean value of σ_{ijt}^2. For a certain group of inserts with unknown wear value, its j-th feature can also be regarded as a normal distribution fuzzy set. It has following the membership function:

$$
B_j(x) = e^{-\frac{(x - \overline{x}_j)^2}{2\sigma_j^2}} \qquad x_j - \sqrt{2}\sigma_j \le x \le x_j + \sqrt{2}\sigma_j
$$
$$
= 0 \qquad \text{for all others} \qquad\qquad \text{........................(2)}
$$

3.3 The approaching degree:

One of the quantitative indexes that represent the fuzzy distance between two fuzzy sets (A and B) is known as the approaching degree. Assume that $\Im(X)$ is the fuzzy power set of a universal set X and the map, N: $\Im(X) \times \Im(X) \rightarrow [0,1]$, satisfies

(1). $\forall A \in \Im(X)$, $N(A,A) = 1$

(2). $\forall A, B \in \Im(X)$, $N(A,B) = N(B,A)$

(3). If $A, B, C \in \Im(X)$ satisfies

$|A(x) - C(x)| \ge |A(x) - B(x)|$ $(\forall x \in X)$ then $N(A,C) \le N(A,B)$

so the map N is the approaching degree in $\Im(X)$ and $N(A,B)$ is called the approaching degree of A and B. It can be calculated by using different methods. Here the inner and outer products are used. Assume that $A, B \in \Im(X)$, so $A \bullet B = \vee\{A(x) \wedge B(x): x \in X\}$ is

defined as the inner product of A and B and $A \oplus B = \wedge\{A(x) \vee B(x): x \in X\}$ is defined as the outer product of A and B. Finally, in the map $N: \mathfrak{T}(X) \times \mathfrak{T}(X) \rightarrow [0, 1]$, $N(A,B)$ is the approaching degree of A and B.

$$N(A,B) = (A \bullet B) \wedge (A \oplus B)^c \qquad\qquad ....(3)$$

3.4 The ANN driven fuzzy pattern recognition algorithm: Using the conventional fuzzy pattern recognition technique, the fuzzy distances (such as approaching degree) between corresponding features of the object to be recognized and the models are first calculated, combining these distances can determine the fuzzy distance between the object and different models. The object should be classified to one of the models that have the shortest fuzzy distance (or highest approaching degree) with it. Because most features have vague boundaries so using fuzzy membership function to represent their characteristics and fuzzy distance to describe the similarity of corresponding features are quite appropriate. Fuzzy pattern recognition techniques are thus quite reliable and robust. They can be further improved by developing a method that can assign suitable weights to all the features to reflect the specific influences of different features in the pattern recognition process. For solving this problem, an advanced ANN driven fuzzy pattern recognition algorithm is developed from this study.

Artificial neural networks (ANNs) have the ability to classify inputs. The weights between neurons are adjusted automatically in the learning process to minimize the difference between the desired and actual outputs. ANN can continuously classify and also update classifications. In this study, ANN is connected with fuzzy logic technique to establish an ANN driven fuzzy pattern recognition algorithm. It's principle is shown in Fig. 4.
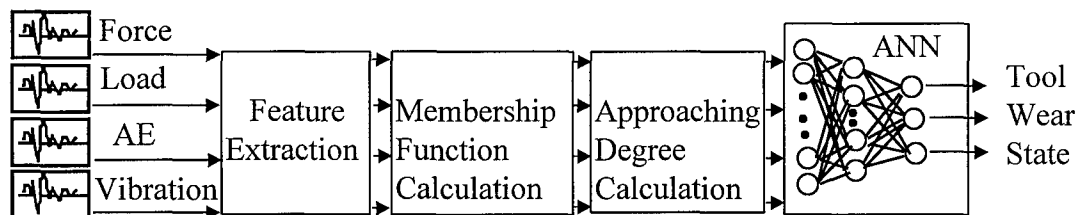

Fig.4 The ANN driven fuzzy pattern recognition algorithm

Here a back propagation ANN is used to carry out tool wear classification. The approaching degree calculation results are the input of the ANN. The associated weights can be updated as: $w_i(new) = w_i(old) + \alpha \delta x_i$. Here α, δ, x_i are learning constant, associated error measure and input to the i-th neuron. In this updating process, the ANN recognizes the patterns of the features corresponding to certain tool wear state. So in practical machining process, the feature pattern can be accurately classified to that of one of the models. In fact ANN assigns each feature a proper synthesized weight and the output of the ANN are weighted approaching degrees. This enables the tool wear

classification process be more reliable. Fig.5 shows the calculation process of tool wear states classification.
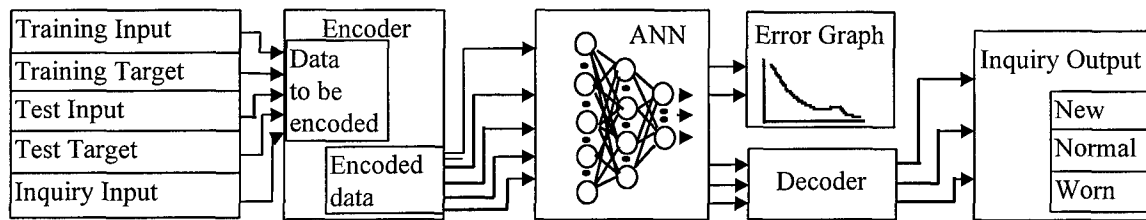

Fig.5 The tool wear states classification process

3.5 Learning: Six standard tool wear values were selected as the models for the future pattern recognition, ranging from new to severe wear where the width of the flank wear area increased from 0 to 0.5 mm in steps of 0.1 mm. Three standard flank wear value, 0, 0.2 mm and 0.5 mm are used to represent new tool, normal tool and worn tool. For each tool with the standard wear value, the membership functions of all its features can be calculated and then stored in a library in the computer. As an example, Table 1 shows the coefficients of some of the features (mean power in ten frequency ranges) of cutting force F_x for three standard models under cutting condition1*, then the membership functions of those features can be determined by using formula (1). These are called the main membership functions

Table 1   Coefficients of the membership function of features of F_x

VB.(mm)=	0			0.2			0.5		
FREQUENCY (kHz)	a_{ij}	b_{ij}	σ_{ij}	a_{ij}	b_{ij}	σ_{ij}	a_{ij}	b_{ij}	σ_{ij}
0~0.2	0.21	0.23	0.007	0.529	0.567	0.017	0.98	0.99	0.082
0.2~0.4	0.152	0.215	0.025	0.371	0.542	0.072	0.723	0.952	0.176
0.4~0.6	0.023	0.055	0.009	0.163	0.306	0.063	0.266	0.367	0.045
0.6~0.8	0.076	0.083	0.011	0.076	0.124	0.023	0.163	0.233	0.037
0.8~1	0.043	0.086	0.016	0.092	0.146	0.063	0.166	0.231	0.036
1~1.2	0.013	0.018	0.003	0.072	0.135	0.031	0.094	0.202	0.053
1.2~1.4	0.011	0.018	0.001	0.076	0.103	0.014	0.046	0.125	0.035
1.4~1.6	0.011	0.017	0.006	0.156	0.216	0.025	0.132	0.263	0.066
1.6~1.8	0.012	0.034	0.011	0.078	0.108	0.017	0.033	0.117	0.035
1.8~2	0.013	0.035	0.009	0.032	0.038	0.027	0.023	0.062	0.017

The training process of the ANN is as the following: by using formula (2) 20 groups of membership functions of all the features for each model can be determined. These are called sub-membership functions. They can represent many sub-models that also have standard tool wear values. Then using equation (3) can decide the approaching degrees between the corresponding features of these sub-models and six models (from new to worn). The results can be used as the training inputs of the ANN. The training targets can be determined like this: the weighted approaching degrees between each model and its own sub-models should be 1 and weighted approaching degrees between a model and other model's sub-models can be calculated by decreasing the value from 1 to zero

linearly. After the training the constructed frame and associated weights of the ANN can reflect the distinct importance of each individual feature for each model under specific cutting conditions. So the tool wear classification results can be reliable and accurate. The determination of the membership functions of all the features for each model and the construction of ANNs for classification mark the end of the learning stage.

3.6 Tool wear classification: In the practical tool condition monitoring process, the tool with unknown wear value is the object and it will be recognized as "new tool", "normal tool" or "worn tool". By using equation (2), the membership functions of all the features of the object can be determined. As an example, Table 2 lists the coefficients of the membership function for the frequency components of the cutting force F_x under cutting condition1*. The flank wear value of this group of inserts is 0.25 mm.

Table 2 Coefficients of the membership function of cutting force F_x

Frequency (kHz)	0~0.2	0.2~0.4	0.4~0.6	0.6~0.8	0.8~1.0	1.0~1.2	1.2~1.4	1.4~1.6	1.6~1.8	1.8~2.0
$\overline{x}_j$	0.561	0.411	0.203	0.088	0.125	0.098	0.079	0.158	0.076	0.035
σ_j	0.025	0.092	0.046	0.029	0.033	0.012	0.024	0.016	0.005	0.006

The approaching degrees of the corresponding features of the standard model and the object to be recognized can be calculated by using equation (3). As an example, Table 3 shows the approaching degrees between part of corresponding features (10 frequency components of the cutting force F_x under cutting condition1*) of a group of inserts (VB=0.25 mm) and three standard models

Table 3 Part of the approaching degree calculating results

Models Frequency (kHz)	0~0.2	0.2~0.4	0.4~0.6	0.6~0.8	0.8~1.0	1.0~1.2	1.2~1.4	1.4~1.6	1.6~1.8	1.8~2.0
VB=0 (mm)	0	0.21	0	0.57	0.47	0.49	0.16	0	0	0.71
VB=0.2(mm)	0.75	0.86	1	0.79	0.93	1	1	0.66	1	0.86
VB=0.5 (mm)	0	0.26	0.49	0.35	0.57	0.52	0.5	0.32	0.53	0.63

The approaching degrees between the corresponding features of the object and different models can be the inquiry input of the ANN. One of a pre-trained ANN is then chosen to calculate the weighted approaching degree between the object and a model under a specific cutting condition. Finally the tool wear state should be classified to the model that has the highest weighted approaching degree with the tool being monitored. In a verifying experiment, fifteen tools with unknown flank wear value were used in milling operations under cutting condition1*. Fig.6 shows the classification results. It can be seen that all the tools were classified correctly with the confidence of higher than 80%. Experiments under other two cutting conditions showed the similar results.
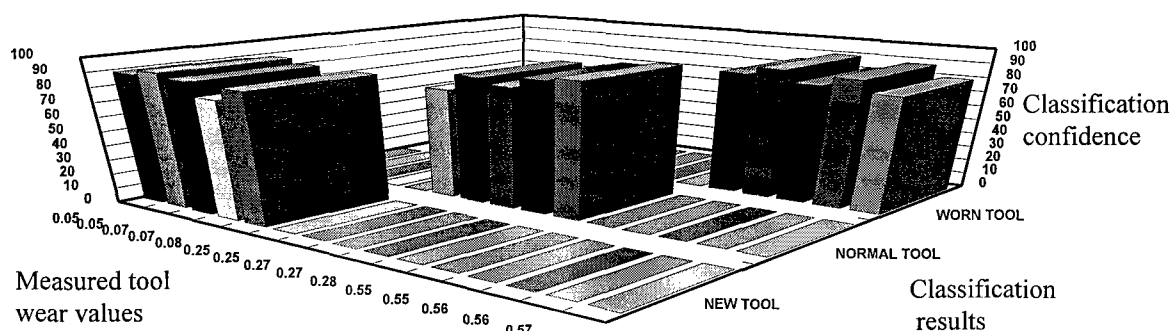
Fig.6 Tool wear states classification results.

4. Conclusions: A methodology has been developed for on-line tool condition monitoring in milling using four kinds of transducers and tool wear relevant features are extracted from the time and frequency domains. Tool wear classification is realized by applying ANN driven fuzzy pattern recognition algorithm. On the basis of this investigation, the following conclusions can be made.

(1) Power consumption, vibration, AE and cutting force sensors are applicable for monitoring tool wear in milling operations. The healthy signals picked up by these sensors within different working frequency ranges describe tool condition comprehensively.

(2) Many features extracted from time and frequency domains are found to be strongly relevant to the changes of tool wear state. This makes accurate and reliable pattern recognition possible.

(3) The combination of ANN and fuzzy logic technique integrates the strong learning and classification ability of the former and the superb flexibility of the latter to express the distribution characteristics of signal features with vague boundaries and the fuzzy distances between them. This methodology indirectly solves the weight assignment problem of the conventional fuzzy pattern recognition system and let it have greater representative power, higher training speed and be more robust.

(4) The ANN driven fuzzy pattern recognition algorithm is effective and suitable for tool wear monitoring. It can carry out the integration and fusion of multi-sensor information. Fuzzy approaching degree can measure the similarity between signal features accurately and the ANN successfully accomplishes the tool wear states classification.

(5). Armed with the advanced pattern recognition methodology, the established intelligent tool condition monitoring system has the advantages of being suitable for different machining environments, robust to noise and tolerant to faults. Accurate tool wear classification can be achieved over a range of machining conditions.

Future work will attempt to identify data processing methods that produce feature vectors describing tool condition more accurately. The ANN driven fuzzy pattern recognition technique will be improved by the application of other forms of fuzzy distances, advanced fuzzy clustering techniques and the optimization of the ANN structure.

* Cutting condition1: cutting speed - 600 rev/min, feed rate - 1 mm/rev, cutting depth - 0.6 mm, workpiece material - EN1A, cutting inserts - Stellram SDHT1204 AE TN-42.

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